Supporting availability evaluation in MCC-based mHealth planning

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The mHealth wearable devices have been adopted in the last few years and have improved the human well-being. However, mobile devices are still quite resource constrained and mHealth applications require high availability. Mobile cloud computing (MCC) is one alternative to aid mobile devices by providing remote powerful infrastructure. The objective is twofold: (i) to identify the most important components of a mHealth system through parametric sensitivity analysis; (ii) to propose and design an extended mHealth architecture with higher system availability and lower downtime period. The proposed solution reduced the downtime in 41% compared with the baseline architecture.

Introduction: An mobile cloud computing (MCC) infrastructure can increase the capacity of mobile devices used in mHealth services. However, the availability of the MCC suffers heavy dependence of its components.

In this Letter, we propose analytical models to represent availability of mHealth systems, adopting a parametric sensitivity analysis to identify critical points that can affect the availability of mHealth services. Therefore, equations were extracted from analytical models such as reliability block diagram (RBD) [1] and continuous time Markov chain (CTMC) [2] and were used to represent and evaluate the proposed service.

The contributions of this work are: (i) hierarchical modelling of the system in mHealth environments using smartwatch in MCC-based mHealth planning; (ii) a sensitivity analysis to find the components that deserve more attention for improving the availability of systems; (iii) analyses of the impact of adopting a redundant components for the proposed service, comparing these results to baseline architecture.

Basic health care cloud architecture: Fig. 1 represents a baseline mHealth cloud-enabled architecture.

Fig. 1 *mHealth baseline cloud architecture*

We distinguish three layers of machines, in increasing order of computational power: the wearable devices (smartwatch), the mobile devices (smartphones/tablets), and the cloud. The wearable devices are used to capture user data and send them to the smartphone via Bluetooth connection. Next, the data are stored in the cloud using internet connection, via WiFi for example.

Availability models: In this section, an analytical mathematical model of RBD and CTMC is represented to evaluate the proposed service. The baseline architecture illustrated in Fig. 1 is represented by the RBD model. Its availability is represented by

$$A_{\mathrm{Sys}} = A_{\mathrm{SW}} \times A_{\mathrm{BT}} \times A_{\mathrm{SP}} \times A_{\mathrm{WF}} \times A_{\mathrm{MC}} \tag{1}$$

Smartwatch (SW), smartphone (SP), and cloud (MC) subsystem block have their availability computed through sub-models, whereas Bluetooth (BT) and WiFi (WF) subsystems are not expanded. If any of the components fails, the whole system will fail, hence the operational mode is represented by:

$$\mathrm{OM}_{\mathrm{Sys}} = \mathrm{SW} \wedge \mathrm{BT} \wedge \mathrm{SP} \wedge \mathrm{WF} \wedge \mathrm{MC}.$$

where SW, BT, SP, WF, and MC are Boolean functions that express the operational status of the respective system components. The system is available only if all subsystems are working properly. Considering that failure and repair times are exponentially distributed, the availability of a component i may be expressed by: $A_i = \lambda_i/(\lambda_i + \mu_i)$.

The number of hours the system is unavailable ($\mathrm{UA} = 1 - A_{\mathrm{Sys}}$) during one year is calculated as: $\mathrm{DTY} = \mathrm{UA} \times 8760$ h.

The smartwatch RBD is represented by five blocks in series: hardware (HW), battery (BR), operating system (OS), application (AP), and sensor (SR). The smartwatch's availability is given by: $A_{\mathrm{SW}} = A_{\mathrm{HW}} \times A_{\mathrm{BR}} \times A_{\mathrm{OS}} \times A_{\mathrm{AP}} \times A_{\mathrm{SR}}$. The smartphone RBD, in turn, is represented by four blocks in series: hardware (HW), battery (BR), operating system (OS), and application (AP). The smartphone's availability is given by: $A_{\mathrm{Sp}} = A_{\mathrm{HW}} \times A_{\mathrm{BR}} \times A_{\mathrm{OS}} \times A_{\mathrm{AP}}$.

The mobile devices' battery autonomy (time required to battery discharge) and its replacement is represented by extracted equations of the CTMC model. The availability of the battery is computed by

$$A_{\mathrm{BR}} = \frac{\lambda}{(\lambda + t \times \mu)} \tag{2}$$

where λ represents the battery discharge rate and μ represents the replacement rate. The discharge is modelled in steps of 10%, with t ($t = 10$) state transitions to reach the fully drained battery state.

The availability of the cloud service is represented by two blocks in series corresponding to the cluster nodes: the web server (WB) and the database servers (DB). Each node is represented by an RBD model with five blocks in series: hardware (HW), operating system (OS), kernel-based virtualisation infrastructure (KVM), virtualised operating system (VM), and the application (AP) running on the virtualised operating system. The nodes availability is represented by equation: $A_{Nd} = A_{\mathrm{HW}} \times A_{\mathrm{OS}} \times A_{\mathrm{KVM}} \times A_{\mathrm{VM}} \times A_{\mathrm{AP}}$, and the availability of the cloud is calculated by the equation: $A_{\mathrm{MC}} = A_{\mathrm{WB}} \times A_{\mathrm{DB}}$.

Table 1 presents the input parameters for the RBD model in (1), where MTTF is the mean time to failure and MTTR is the mean time to recovery. Table 2 presents the input parameters of the CTMC model in (2). The rates for the smartwatch's battery subsystem were obtained through controlled experiments, and for the smartphone battery were obtained from Oliveira *et al.* [3].

Table 1: Input parameters for the baseline architecture [3–5]

Component	MTTF (h)	MTTR (h)
Smartwatch	9.964950	0.081748
Bluetooth	4881.605	0.00953
Smartphone	8.709310	0.081931
WiFi	5.996402	0.078965
Cloud	207.5582046	0.817611

Table 2: Input parameters for the CTMC in (2)

Parameter	λ	μ
Bluetooth	0.9	12
WiFi	1.1	12

We calculated the availability for the baseline architecture. The result was around 96.60%, which corresponds to a downtime of 297.49 h or 12.4 days per year.

Case 1 – sensitivity analysis of architecture: The sensitivity indexes were calculated based on the following equation:

$$\begin{aligned} S_\theta(A) = {} & \frac{\partial A_{\mathrm{SW}}}{\partial\theta} \times A_{\mathrm{BT}} \times A_{\mathrm{SP}} \times A_{\mathrm{WF}} \times A_{\mathrm{MC}} + A_{\mathrm{SW}} \\ & \times \frac{\partial A_{\mathrm{BT}}}{\partial\theta} \times A_{\mathrm{SP}} \times A_{\mathrm{WF}} \times A_{\mathrm{MC}} + A_{\mathrm{SW}} \times A_{\mathrm{BT}} \times \frac{\partial A_{\mathrm{SP}}}{\partial\theta} \\ & \times A_{\mathrm{WF}} \times A_{\mathrm{MC}} + A_{\mathrm{SW}} \times A_{\mathrm{BT}} \times A_{\mathrm{SP}} \times \frac{\partial A_{\mathrm{WF}}}{\partial\theta} \times A_{\mathrm{MC}} \\ & + A_{\mathrm{SW}} \times A_{\mathrm{BT}} \times A_{\mathrm{SP}} \times A_{\mathrm{WF}} \times \frac{\partial A_{\mathrm{MC}}}{\partial\theta} \end{aligned} \tag{3}$$

The failure and repair rates of the SW are defined as λ_{SW} and μ_{SW}, respectively. The corresponding derivative expressions for these rates are given by (4) and (5). The derivative expressions for BT, SP, WF, and MC are similar to those of the SW, since these subsystems are represented by similar RBDs

$$\frac{\partial \mathrm{ASW}}{\partial \lambda_{\mathrm{SW}}} = -\frac{\mu_{\mathrm{SW}}}{(\mu_{\mathrm{SW}} + \lambda_{\mathrm{SW}})^2} \tag{4}$$

$$\frac{\partial \mathrm{ASW}}{\partial \mu_{\mathrm{SW}}} = -\frac{\mu_{\mathrm{SW}}}{(\lambda_{\mathrm{SW}} + \mu_{\mathrm{SW}})^2} + \frac{1}{\lambda_{\mathrm{SW}} + \mu_{\mathrm{SW}}} \tag{5}$$

The index in Table 3 indicates that the WiFi, smartphone, and smartwatch parameters have the highest sensitivity values. The WiFi is the most critical component, which means that WiFi has the greatest impact on the steady-state availability of system. Next, the WiFi parameter values were varied. The effects on availability for such variation can be observed from Figs. 2*a* and *b*.

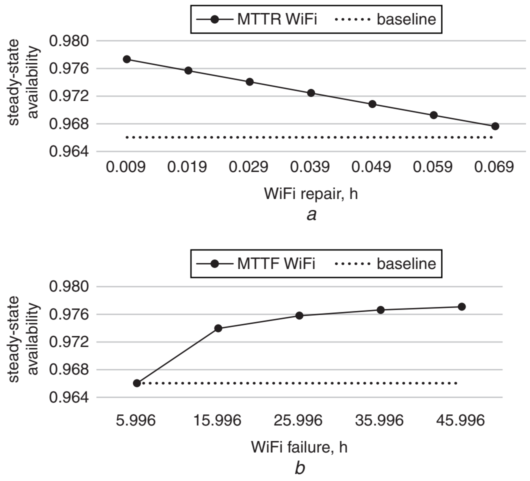

Fig. 2 *Sensitivity analysis of WiFi component*
a Variation WiFi repair
b Variation WiFi failure

Table 3: Sensitivity ranking of availability

Parameter	Sensitivity value
MTTR WiFi	-1.299770×10^{-2}
MTTF WiFi	1.299770×10^{-2}
MTTR smartphone	-9.319631×10^{-3}
MTTF smartphone	9.319631×10^{-3}
MTTR smartwatch	-8.136821×10^{-3}
MTTF smartwatch	8.136821×10^{-3}
MTTF cloud	3.923732×10^{-3}
MTTR cloud	-3.923732×10^{-3}
MTTR Bluetooth	-1.952222×10^{-6}
MTTF Bluetooth	1.952222×10^{-6}

Thus, the MTTR was varied over an interval of 0.078966–0.008966, in increments of 0.01. The baseline availability is 0.966040, but increases to 0.977300 with the shortest repair time. This equates to a 33.16% reduction in downtime. As the MTTF was varied over a range of 5.996402–45.996402, with an increment of 10, the availability is initially 0.966040 and ends with 0.977084, that is, a reduction of 32.52% in downtime.

Case 2 – evaluation impact of the components: Based on the ranking presented in Table 3, we propose and evaluate two possible extensions to the baseline architecture:

(i) *Redundancy on the network interface*, between the smartwatch and the smartphone, adding a Bluetooth/WiFi connection, and between the smartphone and the cloud, adding a 3G/WiFi connection. The operational mode is represented by the expression: $OM = SW \wedge (BT \vee WF) \wedge SP \wedge (3G \vee WF) \wedge MC$.
(ii) *Redundancy on the cloud*, this new scenario adopted a *cloudlet* (a nearby private cloud), its operational mode is expressed by: $OM = SW \wedge (BT \vee WF) \wedge SP \wedge (WF \wedge (CL \vee MC) \vee (3G \wedge MC))$.

The closed-form expression for battery discharge process when using Bluetooth/Wifi or 3G/WiFi is shown in the following equation:

$$A_{BR} = \frac{(1 + t \times P_\lambda + t \times P_\beta) \times \mu}{(D_\lambda \times P_\lambda + D_\beta \times P_\beta + \mu + t \times (P_\lambda + P_\beta) \times \mu)} \qquad (6)$$

The discharge rates are represented in intervals of 10%, with t ($t = 9$) state transitions to reach the fully drained battery state.

P_λ denotes the probability that the smartwatch chooses to use Bluetooth for data transmission instead of WiFi, with probability P_β. The discharge rates are represented by D_λ for Bluetooth and D_β for WiFi.

Similarly, probability that the smartphone using the 3G or the WiFi is represent by P_λ and P_β, respectively. The discharge rates are represented by D_λ for 3G and D_β for WiFi.

Table 4 presents the input parameters of the CTMC model in (6). Fig. 3 presents the availability and downtime over one year for the three presented mHealth architectures.

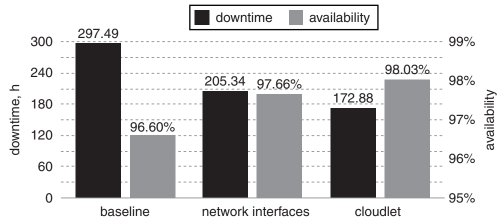

Fig. 3 *Comparison between three mHealth architectures during one year*

Table 4: Input parameters for the battery CTMC model in (6)

Parameter	P_λ	D_λ	P_β	D_β
Bluetooth/WiFi	0.7	0.9	0.3	1.1
3G/WiFi	0.7	1.4	0.3	1.1

The availability of the baseline architecture is 96.60% and the downtime is 297.49 h. When adding multiple network connections, the availability increases about 1.05%, whereas the downtime decreases to 205.34 h (92.14 h or −30% of difference). The results are even more promising when extending the architecture with redundancy on the cloud. In this case, there was a 1.42% increase in the availability and the downtime decreases from 297.49 to 172.88 h (124.61 h or −41% of difference). The cloudlet architecture has shown to be the best option for increasing the availability and consequently the reliability of the mHealth architecture.

Conclusion: In this Letter, we proposed and designed hierarchical RBD and CTMC models to represent and evaluate mHealth systems. We conducted a parametric sensitivity analysis under a minimal architecture; observing the most critical components, we proposed two extended versions of the baseline architecture. The first extended architecture explored multiple network interfaces, while the second one applied the use of cloudlets. The architecture aided by a cloudlet presented the best results in terms of availability and downtime. The cloudlet architecture has achieved 98.03% of availability and 172.88 h of downtime. Future work will address the evaluation of sub-components in more details and analyse variations in the proposed architectures.

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One or more of the Figures in this Letter are available in colour online.

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